Extremely Negative Ratings and Online Consumer Review Helpfulness: The Moderating Role of Product Quality Signals

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Abstract

Contrasting findings about the role of extremely negative ratings (ENRR) are found in the literature, thus suggesting that not all ENRR are perceived as helpful by consumers. In order to shed light on the most helpful ENRR, we have drawn on negativity bias and the signaling theory, and we have analyzed the moderating role of product quality signals in the relationship between ENRR and review helpfulness. The study is based on the analysis of 9,479 online reviews, posted on TripAdvisor.com, pertaining to 220 French hotels. The findings highlight that ENRR is judged as being more helpful when the hotel has been awarded a certificate of excellence, and when the average rating score and the hotel classification are higher. On the basis of these results, we recommend that managers of higher category hotels, with a certificate of excellence and with higher average score ratings, pay more attention to extreme negative judgements.

Keywords: electronic word-of-mouth (eWOM); extreme negative ratings; review helpfulness; Signaling theory; negativity bias; third-party product signals.

1. Introduction

Online consumer reviews (OCRs) are a specific, electronic word-of-mouth (eWOM) type of communication that is increasingly being adopted by large groups of consumers as trusted information to evaluate the quality and performance of products and services they consider buying (Filieri 2015; Sparks, Perkins, and Buckley 2013; Yoo et al. 2009). The integration of eWOM in the purchasing activities of consumers has created an entirely new industry that includes organizations that offer consumers the possibility of rating and reviewing various products and services, ranging from universities to holiday services.

The travel and tourism sector has in particular been impacted by eWOM, as travelers and tourists are influenced to a great extent, in their information search, evaluation and purchase decision, by OCRs (Filieri and McLeay 2014; Filieri 2015; Mauri and Minazzi 2013; Schuckert, Liu, and Law 2015; Sparks and Browning 2011; Vermeulen and Seegers 2009). OCRs and ratings have been found to have considerable effects on the performance of travel and tourism organizations (Mariani, Borghi, and Gretzel 2019; Phillips et al. 2017; Raguseo and Vitari 2017; Tan et al. 2018; Viglia, Minazzi, and Buhalis 2016).

Travelers and tourists are generally willing to rate and review the products or services they have bought. The wide scale adoption of social media and mobile technologies, smart devices and sensors, has contributed to the exponential growth of data (Gretzel et al. 2015). As a result, the number of OCRs has grown to the point that consumers find it difficult to retrieve the information they need to make a purchase decision (Baek, Ahn, and Choi 2012).

However, not all OCRs are considered to be equally helpful by readers, and some are perceived as being more helpful than others. Moreover, the discussion around the factors that influence the helpfulness of OCRs the most is broadening (Filieri 2015; Kwok and Xie 2016; Mudambi and Schuff 2010; Pan and Zhang 2011; S. Park and Nicolau 2015; Shin et al. 2019). Third-party retailers, such as TripAdvisor, enable consumers to express an opinion about the reviews they find the most helpful, with the aim of facilitating consumers in assessing the quality and performance of the proposed products and services. Helpful OCRs have various impacts on business performance, such as e-retailers' sales (Ghose and Ipeirotis 2011), consumers' purchase intentions (Filieri 2015) and travelers' intentions to book a hotel room (L. Wang et al. 2015).

Extremely negative and extremely positive review ratings both play particular roles on the decisions of consumers. By the expression "extremely negative or positive review ratings", we mean the lowest or the highest evaluations in a rating scale, concerning a product or service, given by a reviewer. This evaluation is often indicated, on such websites as TripAdvisor and Airbnb, by means of a numerical scale of stars, ranging from one to five, where a one-star rating indicates an extremely negative review and a five-star rating indicates an extremely positive one.

Contrasting results have been observed in the eWOM literature regarding the role of extreme rating reviews. Extreme reviews have emerged as being less helpful than moderate rating reviews for such experiential goods as video games, music CDs and MP3 players (Cao, Duan, and Gan 2011; Mudambi and Schuff 2010). However, consumers of another kind of experiential goods (i.e. restaurants) have voted extreme reviews as being more helpful than moderate ones (S. Park and Nicolau 2015). On the other hand, Filieri (2016), using a qualitative approach, revealed that several factors may moderate the influence of extreme negative rating reviews on consumer behavior (i.e. the degree of detail, the intensity of emotions in reviews, etc…). Accordingly, scholars have provided evidence that some conditions (e.g. the intensity of emotions in reviews, the consistency of complaints, the type of product) moderate the helpfulness of both positive and negative online reviews (Filieri et al. 2018a; Filieri, Raguseo and Vitari 2019; K.-T. Lee and Koo 2012; M. Lee et al. 2017; Mudambi and Schuff 2010; Wu 2013). From these heterogeneous results, it is possible to conclude that there is still a need to further investigate what makes extreme rating reviews helpful.

We claim that one possible reason that could explain these mixed findings, at least partially, may be the fact that the aforementioned scholars did not measure the influence of factors that could moderate the relationship between extremely negative/extremely positive ratings and review helpfulness in their studies (Fang et al. 2016; Z. Liu and Park 2015; S. Park and Nicolau 2015; Racherla and Friske 2012). Extremely negative and extremely positive reviews are different to the extent that the motivations for posting them and their usage in the consumer decision-making process are also different (Yan and Wang 2018).

In the present study, we integrate the Signaling theory (Boateng 2018; Connelly et al. 2011; Spence 1973, 2002; Steigenberger and Wilhelm 2018) and Negativity Bias (Herr, Kardes, and Kim 1991) to explain the relationship between extremely negative ratings and review helpfulness. Negativity Bias assumes that consumers perceive negative events and information as being more salient, potent, dominant in combinations and, generally, more efficacious than positive events (Herr, Kardes, and Kim 1991; Mizerski 1982; Rozin and Royzman 2001; Wu 2013).

In the eWOM context, negative online reviews are found to be particularly influential in determining the sales of existing and new products (Basuroy, Chatterjee, and Ravid 2003; Chevalier and Mayzlin 2006; Cui, Lui, and Guo 2012). Hence, in this study, we only look at one extreme of the rating scale, extreme negative rating, with the aim of obtaining more precise and robust results.

Apart from calling for more research on the differential impact of positive and negative reviews, researchers have highlighted the need to consider other sources of influence, in addition to reviews and the reviewers' characteristics (Filieri et al. 2018a). Hence, our research was aimed at analyzing under what conditions consumers consider extreme negative rating reviews helpful.

In order to answer this call, we have levered on the Signaling theory (Spence 2002). Signals are visible cues that can be used to communicate the quality of products or services that are generally difficult to evaluate, due to information asymmetries. To reduce information asymmetries, online retailers increasingly provide quality signals (Kirmani and Rao 2018; Mavlanova, Benbunan-Fich, and Koufaris 2012) to help consumers assess the products on offer. We consider user-generated product quality signals, such as review volumes and average hotel ratings, as well as third-party product quality signals, such as the certificate of excellence, as being complementary to the more traditional product quality signals, that is, the hotel category and/or the hotel chain. These quality signals are all displayed on the websites of third-party retailers (e.g. TripAdvisor.com) and, in this study, we have attempted to understand whether they strengthen or attenuate the impact of extremely negative judgments, namely whether they moderate the relationship between extreme negative ratings and review helpfulness. We examined the conditions in which consumers' extreme judgments are more likely to be accepted by other consumers in online settings. We tested our model using a sample of 9,479 OCRs of French hotels published on TripAdvisor. From a managerial perspective, this study may be considered useful for third-party e-retailers, such as Booking.com or Tripadvisor.com, in that it could help them to understand when extreme negative reviews are more helpful for consumers and, in a proactive approach, to filter the available OCRs, in order to give more visibility to the most helpful ones.

2. Theoretical background

2.1 Negativity bias in eWOM

The term eWOM refers to 'any positive or negative statement made by potential, actual, or former consumers about a product or company, which is made available to a multitude of people and institutions via the Internet (Hennig-Thurau et al. 2004, 39). Its availability, through the Internet, makes eWOM more influential and powerful than traditional WOM. Moreover, eWOM can reach a larger number of people more rapidly, and on a global scale. Among the different types of eWOM, online consumer reviews and ratings are prominent, in terms of impact on consumer behavior and organizational performance (Filieri et al. 2018a; Yoo et al. 2009). An OCR is any verbal and/or numerical feedback about a company's product or service published online by someone who claims to have used or purchased the reviewed product (Filieri 2016).

Previous studies on OCRs mainly focused on the message and source characteristics, and on their influence on review helpfulness, that is, the content quality, length, complexity, readability, concreteness, language, linguistic style, enjoyment, review age, photos, rating and extreme ratings (Fang et al. 2016; Filieri et al. 2018a, Filieri, Hofacker, and Alguezaui 2018; Filieri et al. 2019; Kwok and Xie 2016; Z. Liu and Park 2015; Pan and Zhang 2011; S. Park and Nicolau 2015; Schuckert, Liu, and Law 2015; Shin et al. 2019; Yang et al. 2017), or on the reviewer's characteristics, that is, the reviewer's country of origin, gender, status, expertise, reputation, innovativeness and identity disclosure (Fang et al. 2016; Filieri et al., 2018a, b, 2019; Kwok and Xie 2016; Z. Liu and Park 2015; Pan and Zhang 2011; S. Park and Nicolau 2015; Yang et al. 2017), hotel size (Filieri et al. 2018a), and on the managers' replies to complaining customers (Kwok and Xie 2016).

The valence of a consumer's review is the synthesis of the evaluative tone of the message and it can range from extremely positive to extremely negative, passing through the neutral valence (K.-T. Lee and Koo 2012; Mauri and Minazzi 2013). In WOM research, it is suggested that negatively valenced information is less ambiguous, more diagnostic and informative than positive or neutral information (Herr, Kardes, and Kim 1991). These results are explained by considering the negativity bias concept, which assumes that consumers perceive negative events as being more salient, potent, dominant in combinations, and generally more efficacious than positive events (Herr, Kardes, and Kim 1991; Mizerski 1982; Rozin and Royzman 2001). As a consequence of negativity bias, negative information has more weight, a higher impact on a person's impression and attracts the individual's attention more than positive information (Birnbaum 1972; Chevalier and Mayzlin 2006).

Scholars in eWOM research on travel and tourism services have paid attention to the influence of both positive and negative reviews (i.e. valence) on consumer behavior (Vermeulen and Seegers 2009; Ye, Law, and Gu 2009; Sparks and Browning 2011; Mauri and Minazzi 2013; Tsao et al. 2015; Viglia et al. 2016; Filieri et al. 2018a, 2019).

However, less attention has been paid to extreme negative judgements, and in particular to one-star rating reviews. An extremely negative review rating indicates the complete dissatisfaction of a consumer with a company or its products (Chevalier and Mayzlin 2006; Hu, Zhang, and Pavlou 2009). The few studies so far produced in the eWOM research field have revealed mixed findings regarding the role of negative or extreme negative rating reviews. Scholars in the field of marketing and information systems have confirmed the impact of extreme negative rating on book sales, which is higher than extreme positive rating (Chevalier and Mayzlin 2006). However, Mudambi and Schuff (2010) found that extreme ratings are less helpful than reviews with moderate ratings for experiential goods, while Wu (2013) revealed that negative and positive reviews are rated as being equally helpful, thereby revealing that the valence of a customer's review is less important than the quality of the information provided in the review.

In the hospitality research field, Park and Nicolau (2015) found that extreme ratings are voted as being more helpful and enjoyable than moderate ratings, while Liu and Park (2015) revealed that consumers tend to consider positive reviews as being more helpful than moderate and negative reviews. Similarly, Fong et al. (2017) found that extreme reviews predicted review helpfulness. Lee, Jeong, and Lee (2017) showed that negative reviews containing intense emotions are less helpful for consumers. Filieri et al. (2019) revealed that reviewer (i.e. expertise, identity) and review (message) factors (i.e. review length and review readability) moderate the influence of extremely negative reviews.

In short, not all negative reviews are perceived, and thus voted, as helpful. The contrasting findings obtained by these scholars may be due to certain moderating factors that affect the influence of extreme negative ratings. For instance, scholars have shown that some conditions (e.g. intensity of emotions in reviews, consistency of complaints, product type) moderate the helpfulness of both positive and negative online reviews (Filieri et al. 2018a, 2019; K.-T. Lee and Koo 2012; M. Lee et al. 2017; Mudambi and Schuff 2010; Wu 2013). Thus, we argue that the negativity bias only occurs for specific situations, and an analysis of the moderators of the relationship between extreme negative ratings and review helpfulness is therefore needed to advance our knowledge on the topic and to explain these contrasting findings.

2.2 The Signaling theory

The Signaling theory helps one to find the specific situations that attenuate or strengthen the negativity bias. The Signaling theory suggests that signals are observable alterable attributes that can be used by individuals and organizations to communicate (Spence 1973). In business environments, signals, like advertisements, are regularly employed to communicate the quality of products and services that are generally difficult to evaluate due to information asymmetries (Spence 2002). The core of the Signaling theory consists in explaining the various types of existing signals and the situations in which they are used (Mavlanova, Benbunan-Fich, and Koufaris 2012; Spence 2002).

The Signaling theory is particularly useful for online contexts, where the level of uncertainty and risk are higher than for an offline purchase situation, and consumers find it more difficult to evaluate the reliability and quality of a seller's products (Mitra and Fay 2010; Schlosser, White, and Lloyd 2006). Information asymmetries make reliability and quality uncertain for consumers. Hence, in order to reduce such information asymmetries, online retailers use signals to communicate with their customers about the concrete quality levels of the products and services they sell (Kirmani and Rao 2018). Quality signals can be transmitted in many forms, including through the brand name, price (Mitra and Fay 2010), warranty, advertising (Kirmani and Rao 2018) and certificates (Deaton 2004).

Signaling is particularly important in the service context. In fact, the intangibility, variability, perishability, inseparability and non-standardized nature of services make them more difficult to evaluate prior to purchasing than goods (Bansal and Voyer 2000). Evaluating online information helpfulness in the service context (i.e. hospitality) can thus be more important than in a goods context, as the level of quality of a service can only be judged by customers after purchasing and upon consumption (Bansal and Voyer 2000). Thus, estimating the quality of experience goods is a challenging task for a potential customer.

In this study, we argue that product quality signals, displayed by review websites or third-party online retailers, may attenuate or strengthen the influence of extremely negative review ratings. Research suggests that customers often use visual information to support review trustworthiness (Filieri 2016), and consumers can look at product quality signals on third-party online retailers that can help to reduce the information asymmetries they face when evaluating experience goods, such as hotels. The 'traditional' hotel quality signals are those established by governmental agencies, in terms of star category (Martín Fuentes 2016) or affiliation to a brand chain (O'Neill and Xiao 2006). These signals are now combined with a variety of other signals that are available on the websites of third-party online retailers. Accordingly, third-party retailers, like Agoda.com, Tripadvisor.com and Booking.com, use several signals, such as review volume and average hotel rating, to communicate the level of quality of the hotels on offer, by directly levering on the OCR, or indirectly by means of some type of qualitative recognition. Firstly, the use of a numerical scale that averages the scores of all the reviews posted for a hotel - which is visually displayed as a star rating (e.g. 3.0, 3.5, 4.0 and so on) - offers additional signals to potential customers (Öğüt and Taş 2012; Viglia et al. 2016). The number of reviews for each hotel is a signal that provides information about the popularity of the hotel (Chevalier and Mayzlin 2006; Filieri, McLeay, and Tsui 2018; J. Lee, Park, and Han 2008). Moreover, the attempt of these online players to analyze and synthesize the large amount of collected data in a single unequivocal message, via certificates of excellence, is another signal that integrates the star categorization and the brand chain affiliation (Kim, Li, and Brymer 2016) on third-party retailer websites. We here assess the moderating role of all these five signals in the relationship between extreme negative rating and review helpfulness, gathered into three complementary groups: *traditional product quality signals*, represented by the hotel category and affiliation to a brand chain, us*er-generated product quality signals,* measuring review volume and average rating score, and *third-party product quality signals*, such as a certificate of excellence.

3. Hypotheses development

3.1 Review volume

The review volume is a user-generated quality signal, displayed by online retailers, which indicates the overall number of reviews posted by previous customers of a product or a service (Godes and Mayzlin 2004; D.-H. Park, Lee, and Han 2007). A high number of reviews indicates the popularity and, indirectly, the performance of a product (Chevalier and Mayzlin 2006; J. Lee, Park, and Han 2008; Filieri et al. 2018b), namely the number of consumers who have purchased (and reviewed) a product or service. Research has proved that the review volume influences sales (Amblee and Bui 2011; Chevalier and Mayzlin 2006; Y. Liu 2006) and purchase intention (J. Lee, Park, and Han

2008). The presence of a large number of reviews on a product reduces the risks perceived by consumers, since a high number of reviews indicates that a product has been purchased by many people, which reduces the uncertainty around its quality and expected performance (Filieri et al. 2018b).

Specifically, in the hotel industry, previous research demonstrated the positive impact of the number of reviews on the performance of restaurants (Kim, Li, and Brymer 2016), the number of hotel bookings (Ye, Law, and Gu 2009) and on occupancy rates (Viglia et al. 2016).

The volume of reviews may explain why extreme negative rating reviews are helpful. Extreme negative rating reviews are, in general, posted less frequently than negative, positive and extremely positive reviews (Chevalier and Mayzlin 2006; Hu, Zhang, and Pavlou 2009; Wu 2013). The negativity bias theory (Rozin and Royzman 2001) assumes that extreme negative ratings are rare, and thus more attention-catching. The rarity of extreme negative rating reviews makes these reviews stand out from the mass of consumer reviews (Wu 2013), and therefore attract the attention of consumers who give priority to these extreme reviews (Filieri et al. 2019). The attention-catching capacity of an extreme rating is stronger when the total volume of reviews is low, due to the relative scarcity of other comparable, available information (i.e. reviews). Thus, we argue that consumers may perceive extreme negative reviews as being more salient and helpful when the hotel has a low number of reviews (Herr, Kardes, and Kim 1991; Mizerski 1982; Rozin and Royzman 2001). On the contrary, extreme negative reviews may be minimized in the mass of consumer reviews when the quantity of information is high. In this case, individuals may rely on selective information processing strategies (Fischer, Schulz-Hardt, and Frey 2008) and extreme negative reviews may be considered as less salient and impactful. Hence, we hypothesize that:

H1. Extremely negative reviews will be perceived as being more helpful when a hotel has a low review volume.

3.2 Average rating score

The average rating score is a user-generated quality signal and refers to 'the overall evaluation of the reviewers of a product in a specific category, and is generally displayed as the average/mean star ratings beside the product picture' (Filieri 2015, 1264). The average product rating score is a visual information "short-cut" that averages the evaluation of all the customers (or reviewers) of one product and can be particularly useful to compare similar products (e.g., hotels located in the same location in a destination). Such an information shortcut can be considered as a type of categorical crowd opinion, because it classifies products according to the overall evaluation of the reviewers. The average rating score is an important signal that consumers pay attention to when they are in the position of having to evaluate services of uncertain quality. The rating score is an average of all the reviewers' evaluations of a hotel, considering various quality dimensions, including, for example, staff helpfulness, room comfort level and cleanliness, the quality of the facilities, the services that are offered to customers and the value that is provided for the price of the room.

High customer ratings from past customers can create a price premium, because they make online transactions less risky (Ba and Pavlou 2002), and because customers are willing to pay more for a higher-rated service as they expect to receive a higher-quality service (Chevalier and Mayzlin 2006).

Consumers are inclined to use numerical ratings as they are easy to process and may reduce information asymmetry (Viglia et al. 2016). Research on travel and tourism services has not only found that customer ratings affect the information adoption of travelers (Filieri and McLeay 2014) and their purchase intention (Filieri 2015), but also increase the performance of restaurants (Kim, Li, and Brymer 2016) and the sales and prices of hotel rooms (Öğüt and Taş 2012; Tavitiyaman, Zhang Qiu, and Qu 2012; N. Wang et al. 2012).

In this study, we expect that a high rating score will moderate the influence of extremely negative rating reviews. Accordingly, when the rating score is positive and high, extremely negative ratings are rarer, unexpected and more attention-catching because they contrast with the opinion of the majority (Asch 1951). Their divergence from the view of the majority could attract the attention of consumers more, in line with the negativity bias concept (Herr, Kardes, and Kim 1991; Mizerski 1982; Rozin and Royzman 2001). On the other hand, when the average valence of a review is negative (e.g. lower than 3.0), extreme negative reviews could be more frequent, and thus not rare and valuable for consumers. In this case, consumers could expect to read more extreme negative rating reviews and they would therefore not be as attractive and attention-catching as in the previous condition. Hence, we expect that the average rating score will moderate the relationship between extreme negative ratings and their helpfulness. In short, we hypothesize that:

H2. Extremely negative reviews will be perceived as being more helpful when a hotel has a high rating score.

3.3 Certificate of excellence

Apart from customer-generated quality signals and governmental authorities, other organizations categorize and certify the quality of products and services. Certification serves as a reliable signal of the (high) quality of the products or services of an organization (Kim, Li, and Brymer 2016), and empirical evidence has confirmed the advantages of being certificated (Fonseca and Domingues 2017; Giacomarra et al. 2016). For example, the presence of environmental certification influences the attitudes of hotel customers toward hotels (Sparks, Perkins, and Buckley 2013). Consumers are more satisfied with hotels which have environmental management certification (ISO 14001) than with hotels without such certification (Peiró-Signes et al. 2014).

Many third-party online retailers in the travel and tourism sector have started to categorize and certify travel and tourism products (Filieri et al. 2018b). These systems complement the traditional hotel star categorization. Third-party retailers, such as TripAdvisor, Booking and Agoda, provide proprietary certification systems to communicate about the quality of the offered products (Filieri et al. 2018b). They propose symbols, or icons, that are presented by the website in an effort to guide consumers toward some products or services that are recommended on the basis of certain stated criteria. For example, TripAdvisor uses such data as the volume, the valence, the content, the rating, the evolution over time of the reviews and the absence of litigation concerning a hotel (e.g. for content integrity issues or fraudulent activity) to provide a certificate of excellence (TripAdvisor 2018). TripAdvisor's Certificate of Excellence award is one of the most coveted badges of honor for businesses in the travel sector. It can give a hotel a competitive edge over other hotels and more visibility on TripAdvisor. TripAdvisor has been handing out their Certificate of Excellence since 2011 to reward hospitality businesses that consistently provide high service quality standards.

Moreover, these signals have already been considered as statistically significant moderators of the impact of the volume of OCRs on organizational performance for restaurants (Kim, Li, and Brymer 2016). Considering these results, we argue, in this study, that third-party certificates of excellence provide cues about the expected quality of the offer, which may accentuate the helpfulness of an extremely negative rating. Hence, we advance the hypothesis that extreme negative rating reviews about hotels that have received a certificate of excellence are perceived as being more interesting by consumers as they disconfirm their beliefs and expectations about a hotel's quality standards inferred through the certificate of excellence signal. Thus, we propose that the effect of customer evaluation, expressed in terms of extreme negative reviews on review helpfulness, could be strengthened if a hotel has a certificate of excellence. Thus, we hypothesize that:

H3. Extremely negative reviews will be perceived as being more helpful when the hotel has been awarded a certification of excellence.

3.4 Hotel category

The category of a hotel is one of the first signals of quality, assigned by authoritative sources, that customers look at to evaluate the quality of a hotel. "Hotel classification" is a term that is used to indicate the subdivision of the various types of accommodation that are available to a customer into categories using, for example, crowns or stars (Callan 1998). Each category consists of specified facilities and services, such as the number of private bathrooms, the minimum size of the rooms, and/or the provision of food and beverage room service (Callan 1998). The hotel star category is a well-known international scheme in the accommodation sector that represents the quality of a hotel with a number of stars (Abrate, Capriello, and Fraquelli 2011). National rating agencies have been established, in many countries, by local authorities, to evaluate hotels on the basis of their intrinsic qualities and to rank them according to a star scale (Abrate et al. 2011; Narangajavana and Hu 2008). Recent research has shown that the impact of this hotel categorization is reflected, for example, on customer satisfaction (Xu et al. 2017). The classification of hotels can serve as a cue to consumers to create expectations about the level of quality of the service a hotel is offering and of its performance (Viglia et al. 2016). The higher the classification of a hotel is, the higher the customers' expectations about the hotel's service quality (Ariffin and Maghzi 2012; Lu, Ye, and Law 2014; Abrate et al. 2011).

We argue that, as a result of the higher expectations created by a hotel category, a consumer will be more surprised and interested in reading an extremely negative rating review for a higher category than for a lower category hotel, hence the negativity bias. For example, consumers may find extreme negative reviews that complain about the room size of hotels of a higher category (4 and 5 star hotels) more helpful than for lower category hotels. This is because the extreme negative review would contrast with the higher expected level of quality of a higher category organization. This extreme negative rating could create a disconfirmation of the consumers' expectation and thus be more eye-catching and interesting to read. On the grounds of these arguments, we propose considering a hotel's category as a moderator of the relationship between an extreme negative review and review helpfulness, through the following hypothesis:

H4. Extremely negative reviews will be perceived as being more helpful when the hotel category is higher.

3.5 Hotel affiliation to a brand chain

A brand is considered as a primary asset in many industries, because it often provides the first element of differentiation among competitive offerings (Wood 2000). The brand is even more critical in service industries and, as such, in the hospitality industry (Onkvisit and Shaw 1989; Bougoure et al. 2016). The importance of a brand, in the hotel industry, at least partially explains why the industry players have embraced brands and have affiliated to brand chains as a distinguishing component of their marketing strategies (Dev, Morgan, and Shoemaker 1995). Hotels affiliated to a brand chain spend a significant amount of money on marketing campaigns to promote their well-known, high-quality services. Moreover, hotels that belong to a chain are often large, have more features (Chung and Kalnins 2001) and are more innovative than small ones (Orfila-Sintes, Crespí-Cladera, and Martínez-Ros 2005).

Moreover, brands reduce the customers' perceived monetary, social and safety risk when they buy services (Berry 2000). A chained-brand symbolizes the essence of the customers' perception of a hotel chain, and embraces all the tangible and intangible attributes of the business that it refers to. On the one hand, brand chains help hotels to identify and differentiate themselves in the minds of customers (Onkvisit and Shaw 1989; Bougoure et al. 2016). On the other hand, hotel guests rely on brand chain names to reduce the risks that are associated with staying at an unknown hotel (Miguéns, Baggio, and Costa 2008). Thus, the offering of a hotel affiliated to a brand chain is perceived as being characterized by high familiarity and consistent quality standards. This perception, in turn, reduces travelers' uncertainty concerning the purchase process, and consumers will conduct fewer risk-handling activities, such as reading a large number of online reviews, when booking a brand chain hotel room.

The Confirmation-Expectation Theory (Oliver 1980) states that consumers form expectations of a product or service prior to use on the basis of the information they receive. The hotel affiliation to a brand chain is an information signal that creates (high) expectations about the level of quality that can be expected at that hotel. Consequently, extreme negative reviews could attract consumers' attention more as they would disrupt their relative certainty about the level of quality of brand chain hotels. We argue that consumers could hence perceive extreme negative reviews as being more salient than all the other reviews because they disconfirm their expectations of the (high) level of quality provided by hotel chains. However, consumers have fewer expectations regarding the expected service quality for independent hotels that are not affiliated to a brand chain. Moreover, consumers could conduct more risk-handling activities, such as reading a higher number of online reviews, on both sides of the rating scale, because they may be less familiar with hotels that do not belong to a brand chain. All the gradients of the rating scale may be informative for the potential customer, when booking an independent hotel room. Hence, we advance that:

H5. Extremely negative reviews will be perceived as being more helpful when the hotel belongs to a brand chain.

A summary of the research framework and the tested hypotheses is shown in Figure 1.

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4. Methodology

a. Data collection

This study has focused on online consumer reviews of hotels, and we chose TripAdvisor because it is one of the most popular websites publishing OCRs. Additionally, TripAdvisor offers a five-star rating system for posters, which makes it easy to identify reviews with extremely negative ratings, and it is used widely throughout the world and in research on hotel review helpfulness (Fang et al. 2016; Filieri et al. 2018a, 2019; Kwok and Xie 2016; Z. Liu and Park 2015; S. Park and Nicolau 2015), thus facilitating the replicability of our research and the generalizability of our results.

We decided to focus on French hotels because the French hotel industry has the highest number of beds available in Europe (Eurostat 2019), and because France is the most visited destination in Europe and in the World (WorldAtlas 2019).

We collected data on each hotel in the sample from TripAdvisor following a three-step approach. First, we downloaded the list of hotels located in France from IODS-Altares, a database that contains the economic and financial data of French companies. Second, we randomly selected 220 hotels that have been reviewed on TripAdvisor from the extracted population, regardless of their characteristics. Therefore, the data collection process involved a stratified random selection of 220 French hotels from a population of 10,110, and was computed by considering a confidence level of 95 percent and a confidence interval of 7 percent in order to have a representative sample of the population. Third, we gathered the OCRs for each hotel in order to test the hypotheses formulated in this study. We used a sample of 912 extreme negative reviews from a dataset of 9,479 OCRs on hotels written between 2011 and 2015 (Figure 2). We followed a two-step approach to collect data for each hotel in the sample. First, we searched for each hotel page on TripAdvisor.com. Second, we recorded the level of all the variables used in the models for each hotel in a database. We collected these data, including all the OCRs, whatever their language of expression was, from the French version of TripAdvisor for the year 2016. Finally, we analyzed the data using STATA software, version 14.

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b. *Data operationalization*

The dependent variable in our model, review helpfulness (RH), was measured using the logarithmic form of the number of helpful votes received by an online consumer review (Z. Liu and Park 2015). We computed the logarithmic value considering the skewness of the variable plot. The independent variable, extreme negative rating, was measured using a dummy variable, where 1 indicates a one-star rating review, 0 otherwise (Filieri et al. 2019).

The moderator variables considered in this study are: the volume of reviews (RVOL), the average rating score (ARS), the hotel category (Hcat), the presence of a certificate of excellence (CE) and the hotel belonging to a chain (HC). These variables were operationalized considering the number of reviews received by a hotel in one year, the average rating score received by the hotel in one year and the number of stars of the hotel, respectively (Silva 2015); a dummy equal to 1 was used if the hotel had a certificate of excellence on TripAdvisor, 0 otherwise (Kim, Li, and Brymer 2016); and a dummy equal to 1 was used if the hotel belonged to a chain, 0 otherwise (Gazzoli, Palakurthi, and Gon Kim 2008).

As far as the control variables are concerned, we included the dummy variables that refer to the identification numbers (ID) of hotels, each of which identified all the OCRs that referred to one specific hotel, as well as the year in which the review was posted. We were thus able to control for time, by including the variables related to years, and for contextual effects, by including the identification number of each hotel. By doing so, we were able to combine variables that did not change over time in the same model with variables that changed over time.

We also added the characteristics of the source (i.e. the reviewer), such as the "helpful votes received by the reviewer" and the reviewer's "country of origin", as control variables. The first variable was operationalized by the number of reviews posted on TripAdvisor.com, by the reviewer, assessed as helpful by other users (Ghose and Ipeirotis 2011). The second variable was a dummy variable that was equal to 1 when the reviewer was French, 0 otherwise (Filieri et al. 2018a).

Table 1 shows the operationalization of the variables and the references.

--- TABLE 1 HERE ---

c. Data analysis

Adopting the approach used in previous studies (S. Park and Nicolau 2015), we used the Tobit regression model, because of the specific feature of helpful votes (dependent variable) and the censored nature of the sample, to analyze the collected data. This decision was taken for two reasons. First, the dependent variable was bound at the extremes, since travelers may either have voted the review as helpful or unhelpful. In this way, their assessments were extreme. Second, the Tobit model has the advantage of solving any potential selection bias for this type of sample. TripAdvisor does not publicly provide any information about the number of people who read their online reviews; it only provides information about the number of total votes received for a review and its rating. If the probability of being part of a sample is correlated with an explanatory variable, the Ordinary Least Squares (OLS) and Generalized Least Squares (GLS) estimates may be biased (Kennedy 2008). Therefore, this study performed a Tobit regression by analyzing the data and measuring the fit with the likelihood ratio and pseudo R-square value (Smithson and Merkle 2013). The Tobit regression method was also preferred because it does not suffer from the restriction regarding a zero value as a missing value, as the OLS estimate instead does: in this study, the "zero value" of the dependent variable represents the customers' perception of unhelpfulness of the reviews. We included the interaction effects in the models to test for the moderation effect between the extreme negative rating and the four considered moderating variables, by centering the involved variables. The resulting equation, which includes all the tested effects, also tested in different models, is the following:

$$\begin{aligned} \textit{Review helpfulness} &= \beta_1 \textit{Extreme negative rating} + \beta_2 \textit{Review volume} + \beta_3 \textit{Average Rating Score} + \beta_4 \textit{Hotel Category} \\ &+ \beta_5 \textit{Certificate of excellence} + \beta_6 \textit{Chain} + \beta_7 \textit{Extreme negative rating* Review volume} \\ &+ \beta_8 \textit{Extreme negative rating* Average Rating Score} + \beta_9 \textit{Extreme negative rating* Hotel Category} \\ &+ \beta_{10} \textit{Extreme negative rating* Certificate of excellence} + \beta_{11} \textit{Extreme negative rating* Chain} + \beta_{12} X + \varepsilon \end{aligned}$$

where X indicates a set of control variables that could influence review helpfulness.

5. Results

Table 2 and Table 3 show the descriptive statistics of the sample and the correlations between the variables used in the models, respectively. Table 2 shows that 44.8% of the OCRs had at least one helpful vote and that 26.8% of the reviews were written by French people. Furthermore, the considered hotels had an average of 3 stars, 41.6% of the hotels belonged to a chain and 46.20% had a certificate of excellence.

--- TABLE 2 HERE ---

It is possible to observe two interesting findings, in relation to the correlations displayed in Table 3. First, extreme negative ratings are likely to be considered as helpful, thus confirming the results of previous studies (Z. Liu and Park 2015; Filieri et al. 2019). This highlights the greater importance of reviews with a very low rating score than reviews with other rating scores. Second, reviews about a hotel that belongs to a chain are more helpful than those that refer to a hotel that does not belong to a chain. This can be explained by considering that a chain is characterized by a standard brand. However, the reviews on these hotels are more helpful since they enable the reader to understand the particular features of each hotel and compare them with the other hotels that belong to the same chain.

--- TABLE 3 HERE ---

Table 4 shows the results of the Tobit regression analysis. Model 1 contains all the control variables and the first-order independent variables. In order to test the hypotheses, one interaction effect was included in each model from Model 2 to Model 6.

Before running the data analysis, we tested for multicollinearity, which can be an issue in regression analysis (Hair et al. 2010). The analysis showed that all the variables had acceptable VIF values and tolerance levels below the suggested threshold of 10 (Greene 2000). Therefore, multicollinearity did not appear to be an issue. In Hypothesis 1, we argued that extremely negative reviews are voted as helpful when the hotel has a lower number of reviews. Our results have not confirmed this hypothesis, since the effect of the interaction between the extreme negative review variable and the number of reviews received by a hotel is not significant (Model 2). Therefore, Hypothesis 1 has not been supported.

Hypothesis 2 stated that extremely negative reviews are voted as helpful when a hotel has a high rating score. We found a significant effect of the interaction term between extreme negative rating and a hotel's average rating score on review helpfulness, thus supporting Hypothesis 2 (Model 3).

Hypothesis 3 formulated that extremely negative reviews are voted as helpful when a hotel is awarded a certificate of excellence. Our results have confirmed this hypothesis, since the effect of the interaction between the extreme negative review variable and a certificate of excellence on review helpfulness is positive and statistically significant (Model 4).

Hypothesis 4 has also been confirmed. As shown in Model 5, there is a significant and positive interaction effect between extremely negative ratings and the hotel's category on the helpfulness of a review. This means that the effect of extremely negative ratings on review helpfulness is reinforced for higher category hotels. We also observed a negative and significant relationship between an extreme negative review and review helpfulness in Model 5. This result underlines the importance of the category of a hotel in the evaluation of extreme rating helpfulness, because, without such a quality signal, the extreme negative evaluation would not be particularly helpful. This result shows that the lower the category of the hotel is, the less helpful the extreme negative evaluation. This is due to the fact that customers of lower category hotels expect negative evaluations and probably consider other evaluation criteria (e.g. price, location).

In Hypothesis 5, we hypothesized that extremely negative reviews are perceived as being more helpful when the hotel in question belongs to a chain. Since the interaction term was not found to be statistically significant (Model 6), Hypothesis 5 has not been confirmed.

--- TABLE 4 HERE ---

Figure 3 provides a graphical representation of the significant moderating effects found in this study. We used a common method to define high and low values, which is based on the use of values that are one standard deviation above or below the mean (Dawson 2014). Each graph contains two curves that represent the level of review helpfulness, according to the extreme rating of the review, in the case where the moderating variable has a high or low value.

--- FIGURE 3 HERE ---

6. Discussion

We started this work by discussing the mixed results obtained in relation to the influence of extreme negative ratings on review helpfulness. Our study focused on extreme negative rating reviews, which are more likely to be voted as helpful by consumers searching for hotel reviews. The findings confirm the presence of negativity bias (Rozin and Royzman 2001).

We assessed whether the quality signals of traditional and third-party retailers moderate the influence of extremely negative rating reviews, that is, a review with a score of one out of five. We hypothesized that moderating variables may be able to explain the contrasting results obtained in previous studies about the role of review valence (Mudambi and Schuff 2010; S. Park and Nicolau 2015; Wu 2013). Drawing upon Negativity Bias and the Signaling theory, we built a theoretical framework and tested it with 9,479 reviews of 220 French hotels posted on TripAdvisor.com.

In this work, we have advanced our theoretical knowledge of the Signaling theory (Spence 2002) and Negativity Bias (Herr, Kardes, and Kim 1991; Rozin and Royzman 2001; Ahluwalia 2002) in the eWOM context (Wu 2013; Filieri et al. 2019) by discussing how product quality signals affect the evaluation of extreme negative judgements. We found that extreme negative reviews are more helpful for higher category hotels (4 and 5 star-hotels) that have high average rating scores, and which have been awarded a certificate of excellence by a third-party retailer. These three signals communicate high product quality and the consistent satisfaction of their guests, thus, in such a context, an extreme negative judgement is more likely to catch the attention of decision makers and be judged as helpful to evaluate a hotel's quality and performance. Hence, negativity bias occurs online when an extreme negative rating disconfirms the quality signals that create the beliefs and expectations of consumers about the level of quality of the hotel they are planning to book.

In short, this study helps to advance the findings of academic literature on the conditions in which negativity bias is more likely to occur, by highlighting the role of product quality signals provided on third-party online retailer websites. The confirmation–expectation theory (Oliver 1980) can help to explain these findings. Quality signals create high expectations about the expected level of quality and performance of a product. However, the presence of extreme negative judgements creates a strong discrepancy in the consumers' beliefs about the level of quality of the hotel inferred through the quality signal. An extremely negative review is thus more diagnostic and attention-catching in the presence of these signals, because it contradicts the consumers' higher expectations about the level of service quality based on the meanings associated with quality signals. It is therefore paramount for these hotels to pay more attention to any potential discrepancy between what guests expect and what they receive.

Thus, we conclude that negativity bias in eWOM settings is more likely to occur in specific situations, particularly when an extreme negative evaluation creates a disconfirmation of expectations and beliefs with the level of quality inferred through third-party product quality signals (Oliver 1980). An extreme negative rating is more salient and relevant when it is given to a product that is considered to be of superior quality, due to the signals provided on and by third-party retailers. In this situation, extreme negative ratings are judged as being more helpful as they help the customers to discover the negative sides of high quality products.

Moreover, by testing the influence of moderators in the relationship between extreme negative rating and review helpfulness, we also help to advance the literature on the moderators of negative reviews, which had previously investigated the product type (Mudambi and Schuff 2010; Sen and

Lerman 2007), emotion intensity (M. Lee et al. 2017), information quality (Wu 2013), objective information and consumer's subjective knowledge (K.-T. Lee and Koo 2012).

In general, it is possible to conclude that consumers do in fact pay attention to some quality signals, and the results of our study indicate the relevance of three types of signals: *user-generated signals (average rating score)*, *institutional signals (hotel classification)* and *third-party quality signals (certificate of excellence)*. These quality signals seem to influence the consumers' decision making perceptions of extreme negative rating reviews of hotels. We have found that product quality signals, instead of attenuating the influence of an extreme negative rating, increase its helpfulness. This counterintuitive result shows how diagnostic and influential product quality signals and extreme negative ratings are considered by consumers. Thus, the product quality signals investigated in this study can help, at least partially, to explain the contradicting results obtained in previous studies (Z. Liu and Park 2015; Mudambi and Schuff 2010; S. Park and Nicolau 2015; Wu 2013), as they have been found to significantly moderate the impact of an extreme negative rating.

The average rating score on third-party retailer websites is displayed conspicuously in order to shape the customers' expectations of service quality, their attitudes toward hotels and their booking intentions (Mauri and Minazzi 2013). Scholars have proved the effect of an average rating score on the purchase intentions of travelers (Filieri and McLeay 2014; Mauri and Minazzi 2013; Sparks and Browning 2011) and on the occupancy rates of hotels (Viglia et al. 2016). In this study, we have found that an average rating score increases the helpfulness of extreme negative rating reviews. An extreme negative review of a hotel that has obtained a high average rating score attracts the attention of the reader more, because consumers want to know about the negative sides of products that had been considered as excellent by previous customers.

As far as the hotel category is concerned, booking a room in a higher category hotel may involve a higher involvement decision (Viglia et al. 2016), and high involvement enhances the consumers' message elaboration and negative information diagnosticity (Ahluwalia 2002). A hotel's category is considered as a reliable indicator of the level of quality of the service it offers and of its performance (Abrate et al. 2011; Viglia et al. 2016). Thus, negativity bias is more likely to occur in this context.

We have also proved that the certificate of excellence awarded to a hotel by a third-party retailer strengthens the helpfulness of extreme negative rating reviews. Previous studies discussed the role of the certificate of excellence of third parties and found it accentuated the effects of a larger number of reviews on the net sales of restaurants (Kim, Li, and Brymer 2016), while other scholars focused on the role of institutional certifications, such as eco-certification, on purchase intentions (Sparks, Perkins, and Buckley 2013).

In addition, the impact of the extreme negative ratings also varies according to the quality signals of the source. Interestingly, even though we did not hypothesize that the reviewer's reputation signals could affect review helpfulness, we found that the relationship between reviewer's helpful votes and review helpfulness was consistently positive across all the tested models. For instance, the higher the number of helpful votes received by a reviewer was, the higher the helpfulness of his/her extremely negative rating review. It is possible to assume that the number of helpful votes a reviewer has received can signal the level of quality or expertise of the reviewer. Thus, readers assume that the extreme negative rating written by a normally helpful reviewer must be accurate and reliable.

7. Managerial implications

In the present study, we have attempted to explain the role of the moderating factors consumers may be affected by in their evaluation of the helpfulness of extreme negative judgements in eWOM. By providing a list of product quality signals that actually strengthen the helpfulness of extreme negative rating reviews, we help hotel managers understand under which conditions extreme ratings are more likely to be used by consumers in their decision making and potentially influence their purchase decisions.

Online consumer reviews play a strategic role in hospitality and tourism management, especially in promotion, online sales and reputation management (Schuckert, Liu, and Law 2015). In this study, we have highlighted how managers of higher category hotels, or of those hotels that have received a certificate of excellence from a third-party retailer, or have high average score ratings on a third-party retailer website, should pay more attention to extreme negative judgements than those hotels that have not received these awards. They should also promptly attempt to attenuate their impact with appropriate response strategies (Mauri and Minazzi 2013).

Moreover, higher priced hotels, that is, with 3 stars or more, have been found to be at a higher risk, and thus their customers require more time and effort to evaluate the alternative offers that are available, with a high involvement in their decision making. Any extreme negative ratings of these hotels would attract the attention of consumers more, and we therefore suggest that the managers of such hotels should adapt their service quality levels to match the guests' expected performance, on the basis of the quality signals they read on consumer review websites.

It is important that hotel managers who have received a certificate of excellence or who manage higher category establishments attempt to maintain the same (high) quality standards over time in order to avoid gaps between the performance expected by the consumers and the actual performance. The higher the gap is, the higher the guests' dissatisfaction and the greater their motivation to post extreme negative ratings. And, as pointed out in this paper, extreme negative reviews are more negative for those hotels that are associated with high quality signals than for hotels that are not.

8. Limitations and future research

Like all studies, our study is not exempt from certain limitations. The first limitation concerns the sample, that is, the type of product and the platform used in our study. In fact, all the hotels included in our sample are French hotels. Thus, generalizability could be achieved by studying the effects of the signals analyzed in this study in other cultural contexts (e.g. Collectivist countries), and with other product types (e.g. restaurants). Furthermore, our sample included online reviews from 2011 to 2015 posted in TripAdvisor, which, although the largest travel community (and social commerce website) in the travel and tourism field, it is not the only one. Moreover, our data, could be considered, at a first glance, to be old in the rapidly changing eTourism environment. Nonetheless, TripAdvisor still takes into consideration all the variables we took into account: rating, review helpfulness, review volume, hotel rating, certificate of excellence, hotel category and hotel chain. Moreover, the users' experience, concerning rating, commenting on, and judging comments as helpful, is similar to what it was at the time of our data collection. This stability of the signals in the TripAdvisor website over time confirms the meaningfulness and the relevance of our model. Moreover, competitors, such as Booking.com, also exploit a similar rating, review and voting interfaces, thereby confirming that our results and discussions offer a long lasting contribution to science.

An analysis of the helpfulness of signals provided by other websites, such as Booking.com, could be carried out together with a comparison of the degree of trustworthiness and helpfulness of the signals adopted by the different websites.

Moreover, in this study, we have focused on extremely negative rating reviews. However, future studies are recommended to understand the helpfulness of different rating scores, namely extremely positive (rating of 5 out of 5), positive (rating of 4 out of 5), moderate (rating of 3 out of 5) and negative scores (rating of 2 out of 5). Rating scores are among the most important signals consumers use to evaluate the quality and performance of services (Filieri 2015), thus understanding what moderates their influence on the consumers' evaluation of review helpfulness and behavior is of utmost importance to understand the impact of rating scores on the consumers' evaluation of products on online settings.

Finally, the models present an overall R-square value of around 15%. This relatively low value can be explained by considering that some variables, which could explain review helpfulness, were omitted. Previous studies found that textual features, such as the review length and the type of words used in the review affect review helpfulness (Mudambi and Schuff 2010; Kwok and Xie 2016; Z. Liu and Park 2015; Pan and Zhang 2011). Therefore, these variables could also play a role in the hypothesized relationships, and could be fruitfully explored in future research.

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Figures

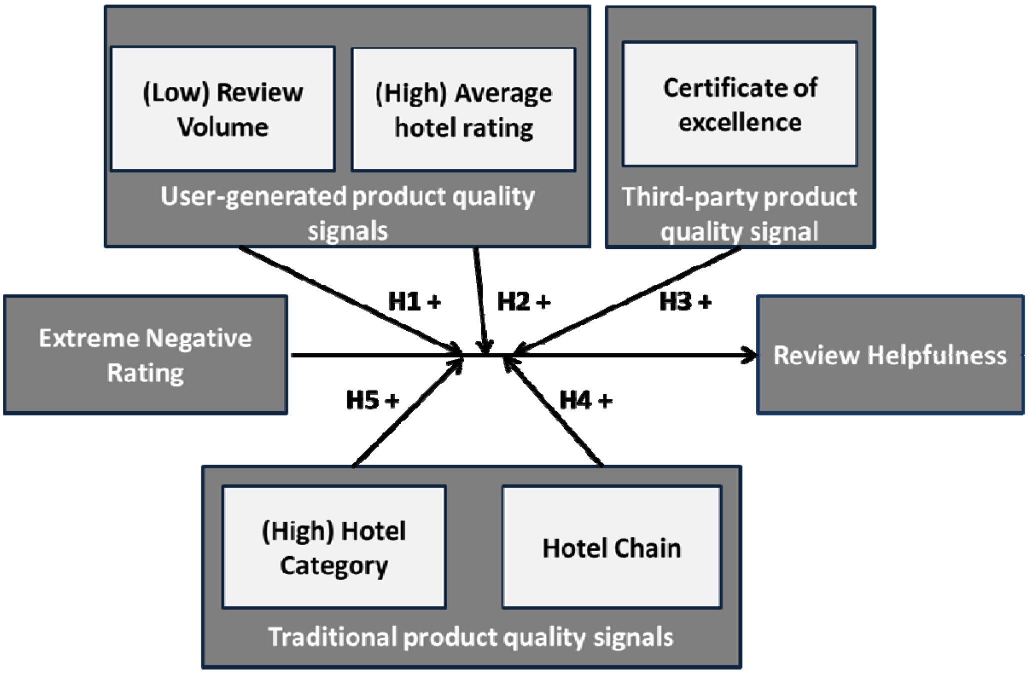

Figure 1. Research framework and hypotheses

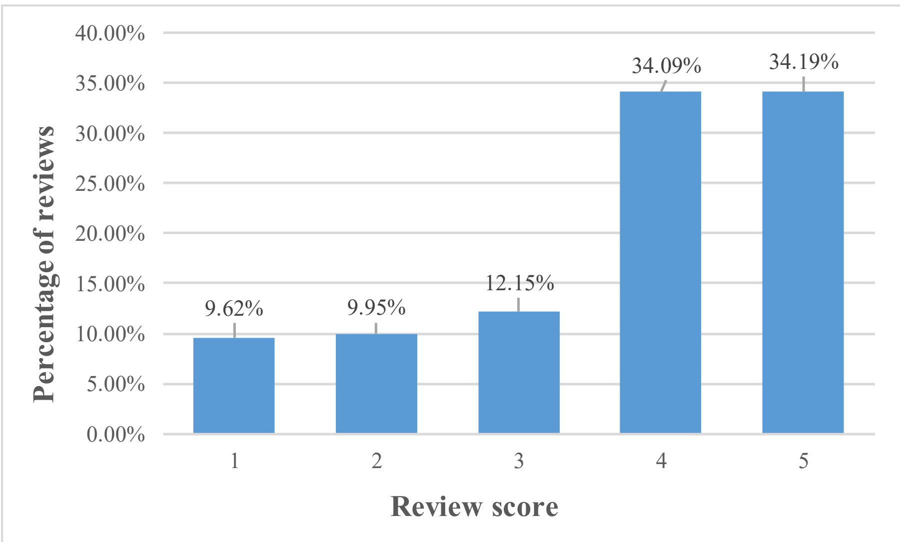

Figure 2. Distribution of the review scores

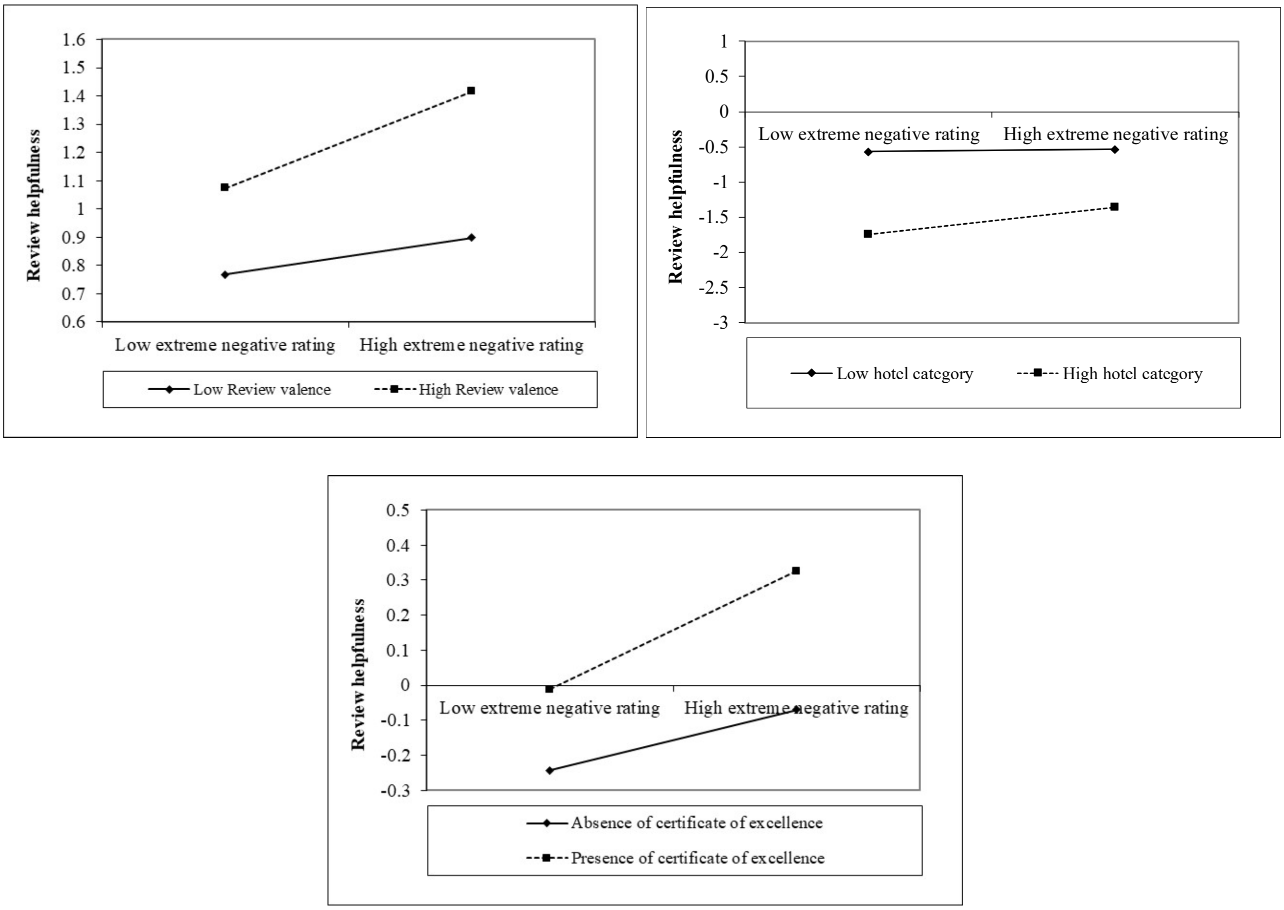

Figure 3. Interaction plots of the significant interaction effects

Tables

Table 1. Variable operationalization

Variable type	Variable name	Operationalization	Reference
Dependent variable	Review Helpfulness (RH)	The number of helpful votes received by an online review in logarithmic form.	(Z. Liu and Park 2015)
Independent variable	Extreme Negative Rating (ENR)	A dummy equal to 1 if the review rating is 1, 0 otherwise.	(Filieri, Raguseo, and Vitari 2019)
Moderator variables	Review Volume (RVOL)	The number of reviews written by customers for a hotel.	(Becerra and Badrinarayanan 2013)
	Average Rating Score (ARS)	The average rating score of the reviews written by customers.	(Filieri 2015)
	Certificate of Excellence (CE)	A dummy equal to 1 if the hotel has a certificate of excellence on TripAdvisor.com, 0 otherwise.	(Kim, Li, and Brymer 2016)
	Hotel Category (HCat)	The number of stars of a hotel.	(Silva 2015)
	Hotel Chain (HC)	A dummy equal to 1 if the hotel belongs to a chain, 0 otherwise.	(Gazzoli, Palakurthi, and Gon Kim 2008)
Control variables	Helpful votes received by the reviewer (HVR)	The number of reviews posted on TripAdvisor.com by reviewers assessed as being helpful by other travelers.	(Ghose and Ipeirotis 2011)
	Country of origin (CO)	Dummy variable equal to 1 when the reviewer is French, 0 otherwise.	(Filieri, Raguseo, and Vitari 2018)
	ID hotel	Dummy variables that refer to the identification number of the hotel that the online review refers to.	n.a.
	Year	Dummy variables that refer to the year in which the review was posted.	n.a.

Note: n.a. stands for not applicable.

Table 2. Descriptive statistics

Variable	**Mean**	**Standard deviation**	**Min.**	**Max.**
Dependent variable				
Review helpfulness (RH)	0.448	0.590	0	3.892
Independent variables				
Extreme negative rating (ENR)	n.a.	n.a.	0	1
Review volume (RVOL)	1.065	4.223	0	61
Average Rating Score (ARS)	n.a.	n.a.	1	5
Hotel Category (HCat)	n.a.	n.a.	1	5
Certificate of excellence (CE)	n.a.	n.a.	0	1
Hotel Chain (HC)	n.a.	n.a.	0	1
Control variables				
Helpful votes received by the reviewer (HVR)	2.148	1.420	0	8.786
Country of origin (CO)	n.a.	n.a.	0	1
ID hotel	104.573	64.281	1	220
Year	n.a.	n.a.	2011	2015

Note: n.a. stands for “not applicable”

Table 3. Spearman correlation matrix

N.	Variable	1	2	3	4	5	6	7	8	9	10	11
1	Review helpfulness (RH)	1.000										
2	Extreme negative rating (ENR)	0.096*	1.000									
3	Helpful votes received by the reviewer (HVR)	0.186*	-0.044*	1.000								
4	Country of origin (CO)	-0.019	0.018	-0.039*	1.000							
5	Hotel Category (HCat)	0.003	-0.193*	0.139*	-0.030*	1.000						
6	Certificate of excellence (CE)	0.075*	-0.309*	0.100*	-0.009	0.246*	1.000					
7	Chain (CH)	0.039*	-0.036*	0.041*	0.032*	0.139*	-0.077*	1.000				
8	ID hotel	-0.002	0.040*	-0.015	0.037*	-0.173*	-0.132*	0.200*	1.000			
9	Year	-0.034*	-0.064*	-0.058*	-0.010	0.049*	0.005	0.100*	0.014	1.000		
10	Review volume (RVOL)	0.078*	-0.100*	0.163*	-0.077*	0.605*	0.412*	0.015	-0.209*	-0.017	1.000	
11	Average Rating Score (ARS)	0.089*	-0.308*	0.171*	-0.052*	0.537*	0.490*	0.078*	0.183*	-0.079*	0.283*	1.000

*Note: * p < 5%.*

Table 4. Results of the Tobit regression analysis. Dependent Variable: Review Helpfulness (RH)

Dependent variable	**RH**	**RH**	**RH**	**RH**	**RH**	**RH**
Model	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
First-order effects						
Extreme negative rating (ENR)	0.382***	0.365***	-0.337	0.319***	-0.359**	0.349***
	(0.051)	(0.063)	(0.243)	(0.057)	(0.174)	(0.070)
Review volume (RVOL)	0.004	0.004	0.002	0.004	0.005	0.004
	(-0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Average rating score (ARS)	0.288	0.289	0.202	0.317	0.328	0.304
	(0.591)	(0.591)	(0.590)	(0.590)	(0.588)	(0.591)
Hotel Category (HCat)	-0.270	-0.274	-0.263	-0.302	-0.422	-0.288
	(0.398)	(0.398)	(0.397)	(0.397)	(0.397)	(0.398)
Certificate of excellence (CE)	0.236	0.234	0.283	0.198	0.206	0.223
	(0.281)	(0.281)	(0.281)	(0.281)	(0.280)	(0.282)
Chain (CH)	-0.006	(-0.010)	0.087	-0.0491	-0.057	-0.029
	(0.550)	(0.550)	(0.550)	(0.550)	(0.547)	(0.551)
Second-order effects						
ENR x RVOL	…	0.003 (0.007)	…	…	…	…
ENR x ARS	…	…	0.191*** (0.063)	…	…	…
ENR x CE	…	…	…	0.297** (0.122)	…	…
ENR x HCat	…	…	…	…	0.226*** (0.051)	…
ENR x CH	…	…	…	…	…	0.068 (0.100)
Control variables						
Helpful votes received by the reviewer (HVR)	0.220***	0.220***	0.218***	0.219***	0.216***	0.220***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Country of origin (CO)	0.007	0.007	-0.164***	0.006	0.012	0.006
	(0.035)	(0.035)	(0.019)	(0.035)	(0.035)	(0.035)
ID hotel	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included
Constant	-0.094	-0.086	0.221	-0.104	0.213	-0.097
	(1.537)	(1.537)	(1.536)	(1.534)	(1.529)	(1.537)
Pseudo R Squared	14.14%	14.19%	14.48%	14.38%	14.82%	14.20%
Hypothesis tested		H1	H2	H3	H4	H5
Hypothesis supported?		No	Yes	Yes	Yes	No

*Note: *** p<0.01, ** p<0.05, * p<0.1; control variables are omitted in the table and are available upon request.*